# Accelerating Fast Fourier Transform with half-precision floating point hardware on GPU

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#### BACKGROUND INFORMATION

Our project concerns a new implementation of the classical discrete Fourier Transform and the fast Fourier Transform algorithm.

### Discrete Fourier Transform

Converts time domain signals to frequency domain signals according to the equation:

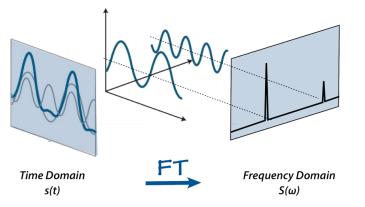
$$X(k) = \sum_{n=0}^{N-1} x(n) \cdot e^{-j\left(\frac{2\pi}{N}\right)nk}$$

приноно п.

- Convolution
- Filtrering
- Image Processing

Inverse DFT:

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) \cdot e^{j \left(\frac{2\pi}{N}\right) nk}$$



Source: MRI Questions http://mriquestions.com/fourier-transform-ft.html

#### Discrete Fourier Transform

DFT can also be represented in matrix form:

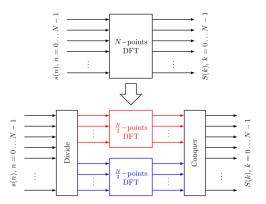
$$X[k] = \sum_{n=0}^{N-1} x[n] \cdot W_N^{kn} \qquad W = e^{-j2\pi/N}$$

$$\begin{bmatrix} X[0] \\ X[1] \\ X[2] \\ \vdots \\ X[N-1] \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & W_N^1 & W_N^2 & \cdots & W_N^{(N-1)} \\ 1 & W_N^2 & W_N^4 & \cdots & W_N^{2(N-1)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & W_N^{(N-1)} & W_N^{2(N-1)} & \cdots & W_N^{(N-1)^2} \end{bmatrix} \begin{bmatrix} x[0] \\ x[1] \\ x[2] \\ \vdots \\ x[N-1] \end{bmatrix}$$

Linear Transformation!

## The Fast Fourier Transform

#### **Divide and Conquer Principle**



Source: DSPlib http://en.dsplib.org/content/fft\_introduction/fft\_introduction.html

FFT Computation requires:  $\sim N*log(N)$  whereas DFT: N^2

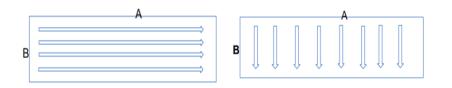
#### 4 Step Algorithm

Data represented as B by A matrix 1. Perform B number of A-point FFT (in parallel, stride B)

2. Perform scaling by twiddle factors exp(- $(2\pi/N)*j*k*I$ )

3. Perform A number of B-point FFT (in parallel, stride 1)

4. Transpose data to form A by B matrix



### Example Problem - DFT

$$W = \begin{bmatrix} \omega^{0} & \omega^{0} \\ \omega^{0} & \omega^{1} & \omega^{2} & \omega^{3} & \omega^{4} & \omega^{5} & \omega^{6} & \omega^{7} \\ \omega^{0} & \omega^{2} & \omega^{4} & \omega^{6} & \omega^{8} & \omega^{10} & \omega^{12} & \omega^{14} \\ \omega^{0} & \omega^{3} & \omega^{6} & \omega^{9} & \omega^{12} & \omega^{15} & \omega^{18} & \omega^{21} \\ \omega^{0} & \omega^{4} & \omega^{8} & \omega^{12} & \omega^{16} & \omega^{20} & \omega^{24} & \omega^{28} \\ \omega^{0} & \omega^{5} & \omega^{10} & \omega^{15} & \omega^{20} & \omega^{25} & \omega^{30} & \omega^{35} \\ \omega^{0} & \omega^{6} & \omega^{12} & \omega^{18} & \omega^{24} & \omega^{30} & \omega^{36} & \omega^{42} \\ \omega^{0} & \omega^{7} & \omega^{14} & \omega^{21} & \omega^{28} & \omega^{35} & \omega^{42} & \omega^{49} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & \omega & -i & -i\omega & -1 & -\omega & i & i\omega \\ 1 & -i\omega & i & \omega & -1 & i\omega & -i & -\omega \\ 1 & -i\omega & i & -1 & -i & 1 & i & -1 & -i \\ 1 & i\omega & i & -\omega & -1 & -i\omega & -i & \omega \end{bmatrix}$$

where

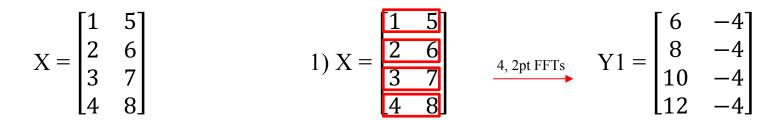
$$\omega=e^{-rac{2\pi i}{8}}=rac{1}{\sqrt{2}}-rac{i}{\sqrt{2}}$$

Matrix Multiplying x and W,

x = [1, 2, 3, 4, 5, 6, 7, 8]

 $\mathbf{X} = [36, 4 + 9.7i, -4 + 4i, -4 + 1.7i, -4, -4 - 4i, -4 - 9.7i]$ 

## Example Problem - FFT



2) Twiddle Factor 3)

$$W = \begin{bmatrix} W^{0*0} & W^{0*1} \\ W^{1*0} & W^{1*1} \\ W^{2*0} & W^{2*1} \\ W^{3*0} & W^{3*1} \end{bmatrix}$$
$$Y2 = \begin{bmatrix} 6 \\ 8 \\ 10 \\ 12 \end{bmatrix} \begin{bmatrix} -4 \\ -2.8 + 2.8i \\ 4i \\ 2.8 + 2.8i \end{bmatrix} \underbrace{-2.4 \text{pt FFT}}_{-4} Y1 = \begin{bmatrix} 36 & -4 + 9.7i \\ -4 + 4i & -4 + 1.7i \\ -4 & -4 - 1.7i \\ -4 - 4i & -4 - 9.7i \end{bmatrix}$$

#### RESEARCH GOALS

- To utilize the tensor core hardware by NVIDIA
- To implement computational tricks
- To consider domain-specific requirements

## Volta Architecture

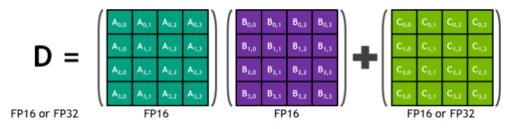
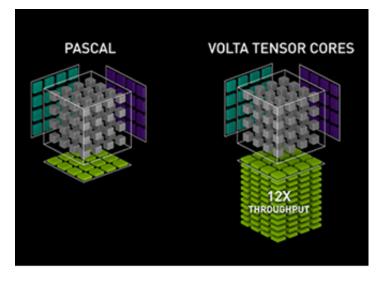


Figure 1. Tensor core 4\*4\*4 matrix multiply and accumulate. Source: https://devblogs.nvidia.com/programming-tensor-cores-cuda-9/

Tensor cores give a 8x increase in throughput using half precision input. This has been utilized by cuBLAS and cuDNN library to accelerate matrix multiplication and artificial intelligence training.



Source: https://www.nvidia.com/en-us/data-center/tensorcore/

## Challenge

The representation range of FP16 is roughly  $6*10^{(-5)}$  to  $6*10^{5}$ , which is much more limited than single precision. This degrades the precision of operations and may cause frequent overflows.

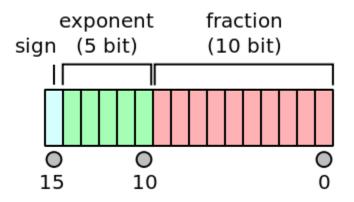


Figure 1. Half precision floating point (FP16) number representation. Source: https://en.wikipedia.org/wiki/Half-precision\_floating-point\_format

## Single to Half Precision

To keep the accuracy, we split a FP32 number to the scaled sum of two FP16 number, and make use of the property that Fourier Transform is a linear operation:

where scaling factor s1 and s2 are determined by the maximum absolute value in the original vector.

## **GPU** Implementation

We first wrote Matlab code to test the algorithm, and will proceed to implement it with C and CUDA. We call cuBLAS library for matrix-matrix multiplication.

cublasGemmEx(handle, CUBLAS\_OP\_N, CUBLAS\_OP\_N, 4, 4, 4, &s1, F4\_re, CUDA\_R\_16F, 1, X\_re, CUDA\_R\_16F, 1, 0, FX\_re, CUDA\_R\_16F, 1, CUDA\_R\_16F, CUBLAS\_GEMM\_DEFAULT)

## Further acceleration

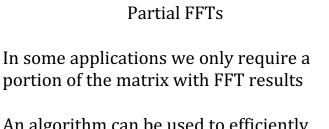
3M algorithm, 2D fft & in-place transformation, partial FFTs

3M Algorithm

$$z = (a + ib)(c + id) = ac - bd + i(ad + bc)$$

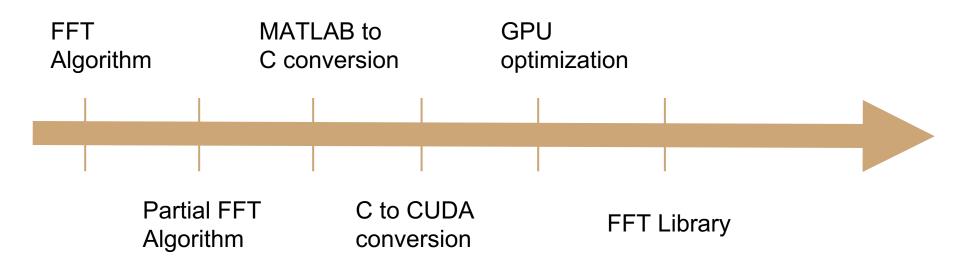
$$z = ac - bd + i \big[ (a+b)(c+d) - ac - bd \big]$$

$$\begin{split} T_1 &= A_1 B_1, \qquad T_2 = A_2 B_2, \\ C_1 &= T_1 - T_2, \\ C_2 &= (A_1 + A_2) (B_1 + B_2) - T_1 - T_2 \end{split}$$



An algorithm can be used to efficiently compute only required portions instead of usual method of computing all and discarding unnecessary FFT values

## Current Progress & Future Work





Any questions?